

Generic Demand Model Considering the Impact of Prosumers for Future Grid Scenario Analysis

Hesamoddin Marzooghi, *Graduate Student Member, IEEE*, Shariq Riaz, *Graduate Student Member, IEEE*, Gregor Verbič, *Senior Member, IEEE*, Archie C. Chapman, *Member, IEEE*, and David J. Hill, *Life Fellow, IEEE*

Abstract—The increasing uptake of residential PV-battery systems is bound to significantly change demand patterns of future power systems and, consequently, their dynamic performance. In this paper, we propose a generic demand model that captures the aggregated effect of a large population of price-responsive users equipped with small-scale PV-battery systems, called *prosumers*, for market simulation in future grid scenario analysis. The model is formulated as a bi-level program in which the upper-level unit commitment problem minimizes the total generation cost, and the lower-level problem maximizes prosumers' aggregate self-consumption. Unlike in the existing bi-level optimization frameworks that focus on the interaction between the wholesale market and an aggregator, the coupling is through the prosumers' demand, not through the electricity price. That renders the proposed model market structure agnostic, making it suitable for future grid studies where the market structure is potentially unknown. As a case study, we perform steady-state voltage stability analysis of a simplified model of the Australian National Electricity Market with significant penetration of renewable generation. The simulation results show that a high prosumer penetration changes the demand profile in ways that significantly improve the system loadability, which confirms the suitability of the proposed model for future grid studies.

Index Terms—Demand response, aggregators, prosumers, PV-battery systems, generic demand model, future grids, scenario analysis, bi-level optimization.

NOMENCLATURE

\mathcal{B}	Set of buses.
\mathcal{G}	Set of generators g .
\mathcal{M}	Set of demand aggregators m .
\mathcal{L}	Set of lines: $\mathcal{L} \subseteq \mathcal{B} \times \mathcal{B}$.
\mathcal{R}	Set of regions r .
\mathcal{H}	Set of time slots h .
\underline{x}/\bar{x}	Minimum/maximum value of x .
$r_g^{+/-}$	Ramp-up/down rate of supplier g .
$\tau_g^{u/d}$	Minimum up/down time of supplier g .
$B_{i,j}$	Susceptance of line between buses i and j .
$\theta_{i,h}$	Voltage angle at bus i in h .
$p_{l,h}^{i,j}$	Power flow on line i - j : $p_{l,h}^{i,j} = B_{i,j}(\theta_{i,h} - \theta_{j,h})$.
$\Delta p_{l,h}^{i,j}$	Power loss on line i - j .

$p_{g,h}$	Generated power of supplier g in h .
$p_{b,h}^m$	Battery storage power of aggregator m in h .
$e_{b,h}^m$	Battery storage state of charge of aggregator m in h .
$p_{d,h}^{inf,m}$	Inflexible demand of aggregator m in h .
$p_{d,h}^{flex,m}$	Flexible demand of aggregator m in h .
$p_{d,h}^{u,m}$	Underlying prosumer demand of aggregator m in h .
$p_{pv,h}^m$	PV generation of aggregator m in h .
$p_{r,h}^{res}$	Required reserve in region r in the system in h .
$s_{g,h}$	Binary decision variable on/off status of supplier g .
$u_{g,h}$	Binary start-up decision variable of supplier g .
$d_{g,h}$	Binary shut-down decision variable of supplier g .
$c_g^{fix/var}$	Fix/variable cost of supplier g .
$c_g^{su/sd}$	Start-up/shut-down cost of supplier g .
η_b	Battery round-trip efficiency.

I. INTRODUCTION

POWER systems are undergoing a major transformation driven by the increasing uptake of variable renewable energy sources (RES). At the demand side, the emergence of cost-effective “behind-the-meter” distributed energy resources, including on-site generation, energy storage, electric vehicles, and flexible loads, and the advancement of sensor, computer, communication and energy management technologies are changing the way electricity consumers source and consume electric power. Indeed, recent studies suggest that rooftop PV-battery systems will reach retail price parity from 2020 in the USA grids and the Australian National Electricity Market (NEM) [1]. A recent forecast by Morgan Stanley has suggested that the uptake can be even faster, by boldly predicting that up to 2 million Australian households could install battery storage by 2020 [2]. This has been confirmed by the Energy Networks Australia and the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO) who have estimated the projected uptake of solar PV and battery storage in 2050 to be 80 GW and 100 GWh [3], which will represent between 30%–50% of total demand, a scenario called “Rise of the Prosumer” [4]. Here, the *prosumer* they refer to is a small-scale (residential, commercial and small industrial) electricity consumer with on-site generation. A similar trend has been observed in Europe as well [5]. Given this, it is expected that a large uptake of demand-side technologies will significantly change demand patterns in future grids¹, which will in turn affect their dynamic performance.

¹We interpret a *future grid* to mean the study of national grid type structures with the above-mentioned transformational changes for the long-term out to 2050.

Hesamoddin Marzooghi, Shariq Riaz, Gregor Verbič, Archie C. Chapman, and David J. Hill are with the School of Electrical and Information Engineering, The University of Sydney, Sydney, New South Wales, Australia. e-mails: (hesamoddin.marzooghi, shariq.riaz, gregor.verbic, archie.chapman, david.hill@sydney.edu.au).

Shariq Riaz is also with the Department of Electrical Engineering, University of Engineering and Technology Lahore, Lahore, Pakistan.

David J. Hill is also with the Department of Electrical and Electronic Engineering, The University of Hong Kong, Hong Kong.

Existing future grid feasibility studies [6]–[10] typically use conventional demand models, possibly using some heuristics to account for the effect of emerging demand-side technologies, and the synergies that may arise between them. They also assume specific market arrangements by which RES are integrated into grid operations. The challenge associated with future grid planning is that the grid structure and the regulatory framework, including the market structure, cannot be simply assumed from the details of an existing one. Instead, several possible evolution paths need to be accounted for. Future grid planning thus requires a major departure from conventional power system planning, where only a handful of the most critical scenarios is analyzed. To account for a wide range of possible future evolutions, *scenario analysis* has been proposed in many industries, e.g. in finance and economics [11], and in energy [12]–[14]. As opposed to power system planning where the aim is to find an optimal transmission and/or generation expansion plan, the aim in scenario analysis is to analyze possible evolution pathways to inform policymaking. Given the uncertainty associated with long-term projections, the focus of future grid scenario analysis is limited to the analysis of what is technically possible, although it might also consider an explicit costing [15]. Our work is part of the Future Grid Research Program funded by the CSIRO, whose aim is to explore possible future pathways for the evolution of the Australian grid out to 2050 by looking beyond simple balancing. To this end, a comprehensive modeling framework for future grid scenario analysis has been proposed in [16], which includes a market model, power flow analysis, and stability analysis. The demand model, however, assumes that the users are price-takers, which doesn't properly capture the aggregated effect of prosumers on the demand profile, as discussed later.

A. Related Work

Due to the influence of a demand profile on power systems performance and stability, recent studies have attempted to integrate the aggregated impact of prosumers into the demand models [17]–[22]. The focus, however, is usually on scheduling of particular emerging demand-side technologies, e.g. HVAC [17]–[19], flexible loads [20], PV-battery systems [21], and plug-in electrical vehicles (PEVs) [22]. Most of these modeling approaches assume an existing market structure, with the impact of prosumers incorporated by allowing demand and supply to interact in some limited or predefined ways. Specifically, this is mainly done via three different approaches:

- 1) Only the supply-side is modeled physically while prosumers are considered by a simplified representation of demand-side technologies. In [20], flexible loads' effects on reserve markets are analyzed by modeling prosumers with a tank model; however, the reserve market is greatly simplified. In [17], prosumers are represented by a price-elasticity matrix, which is used to model changes in the aggregate demand in response to a change in the electricity price, and are acquired from the analysis of historical data.

- 2) Demand-side technologies are physically modeled while a simplified representation of supply-side is employed. For instance, in [21], the supply-side is represented by an electricity price profile.
- 3) Both supply and demand sides can be modeled physically and optimized jointly, as in [18], [22], which can produce more realistic results. For example, the study in [22] integrates the aggregated charging management approaches for PEVs into the market clearing process, with a simplified representation of the latter.

Although the above models have shown their merits, they are dependent on specific practical details such as the electricity price or the implementation of a mechanism for demand response (DR) aggregation, which limits their usefulness for future grid scenario analysis where the detailed market structure is potentially unknown.

Against this backdrop, the paper proposes a principled method for generic demand modeling including the aggregated effect of prosumers. The model is formulated as a bi-level program in which the upper-level unit commitment problem minimizes the total generation cost, and the lower-level problem maximizes the *aggregate* prosumers' self-consumption. In more detail, the lower-level objective is motivated by the emerging situation in Australia, where rooftop PV owners are increasingly discouraged from sending power back to the grid due to very low PV feed-in-tariffs versus increasing retail electricity prices. In this setting, an obvious cost-minimizing strategy is to install small-scale battery storage, to maximize self-consumption of local generated energy and offset energy used in peak pricing periods. Similar tariff settings appear likely to occur globally in the near future, as acknowledged in [23]. Moreover, self-consumption within an aggregated block of prosumers is a good approximation of many likely behaviors and responses to other future incentives and market structures, such as (peak power-based) demand charges, capacity constrained connections, virtual net metering across connection points, transactive energy and local energy trading, and a (somewhat irrational) desire for self-reliance.

A key difference from existing bi-level optimization frameworks is that in our formulation, the levels are coupled through the prosumers' demand, not through the electricity price. In contrast, other models, which focus on the interaction between an aggregator and the prosumers [19] or the aggregator and the wholesale market [22], couple the levels through prices. These approaches essentially define a market structure, that is, a pricing rule to support an outcome. In contradistinction, our proposed model is market structure agnostic. That is, it implicitly assumes that an efficient mechanism for demand response aggregation is adopted, with prices determined by that unspecified mechanism, which support the outcomes computed by our optimization framework.

The paper builds on our previous work [24], [25]. In [25], we have assumed that a prosumer aggregation represents a homogeneous group of loads; that is, we have assumed that they all behave in the same way and have the same capacity, and are allowed to send power back to the grid. In the absence of an explicit transmission pricing, this can create perverse outcomes, such as power exchange between

aggregators located in different parts of the network. In the model proposed in this paper, the aggregators are not allowed to send the power back to the grid, which better models the assumption of self-consumption within an aggregated block of prosumers. The model proposed in [24] is similar to the model in this paper, however, the prosumer battery storage is modeled implicitly, which requires a heuristic search to capture the prosumer behavior.

The remainder of the paper is organized as follows: Section II presents the proposed modeling framework. In Section III, the efficacy of the proposed framework is demonstrated on a simplified 14-generator network model of the NEM with a significant RES penetration. Finally, Section IV concludes.

II. GENERIC DEMAND MODEL CONSIDERING THE IMPACT OF PROSUMERS

Generic demand models are essential for power system studies. They are commonly used to reflect the aggregated effect of numerous physical loads [26], [27]. Conventional demand models only account for the accumulated effect of independent load changes and some relatively minor control actions, that is, they are by necessity simplified to not include all details of the loads. In the following, we explain the motivation behind this work and the modeling assumptions.

A. Research Motivation and Modeling Assumptions

The main purpose of developing generic demand models is to provide accurate dispatch decisions for balancing and stability analysis of future grid scenarios. Given the uncertainty associated with future grid studies, the modeling framework should be market structure agnostic, and capable of easy integration of various types and penetrations of emerging demand-side technologies. To this effect, we make the following assumptions:

- 1) The loads are modeled as price anticipators. In our previous work [16], [28], we modeled the loads as price-takers, inspired by the smart home concept [29], in which the loads respond to the electricity price to minimize energy expenditure. The study has shown that with large penetration of price-taking prosumers, the marginal benefit might become negative when secondary peaks are created due to the load synchronization (see Fig. 1 showing the operational demand with different penetrations of prosumers). Therefore, demand response aggregators (henceforth simply called aggregators) have started to emerge to fully exploit the demand-side flexibility. To that effect, the model implicitly assumes an efficient mechanism for demand response aggregation (an interested reader might refer to [30] for a discussion on practical implementation issues). However, specific implementation details, like price structure or the division of the profit earning by the aggregated collection of prosumers, are not of explicit interest in the proposed model.
- 2) The demand model representing an aggregator consists of a large population of prosumers connected to an unconstrained distribution network who collectively max-

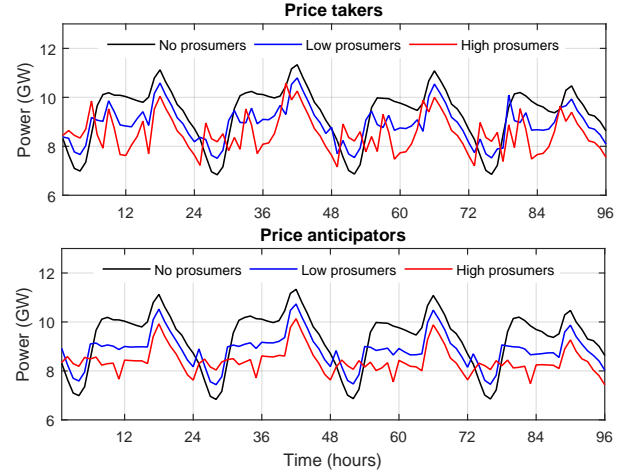


Fig. 1. Operational demand with different penetrations of price-taking (top) and price-anticipating prosumers (bottom).

imize self-consumption (made possible by an efficient internal trading and balancing mechanism).

- 3) Aggregators do not alter the underlying energy consumption of the prosumers. That is, except for battery losses the total energy consumption before and after aggregation remain the same; however, the power profile does change, by employing storage technologies.
- 4) Prosumers have smart meters equipped with home energy management (HEM) systems for scheduling of the PV-battery systems. Also, a communication infrastructure is assumed that allows a two-way communication between the grid, the aggregator and the prosumers, facilitating energy trading between prosumers in the aggregation.

These assumptions appear to be appropriate for scenarios arising in time frame of several decades into the future.

B. Bi-level Optimization Framework

In the model, we are specifically interested in the aggregated effect of a large prosumer population on the demand profile, assuming that the prosumers collectively maximize their self-consumption. Given that the objective of the wholesale market is to minimize the generation cost, the problem exhibits a bi-level structure. In game theory, such hierarchical optimization problems are known as Stackelberg games. They can be formulated as bi-level mathematical programs of the form [19]:

$$\begin{aligned}
 & \underset{\mathbf{x}, \mathbf{y}}{\text{minimize}} && \Phi(\mathbf{x}, \mathbf{y}) \\
 & \text{subject to} && (\mathbf{x}, \mathbf{y}) \in \mathcal{Z} \\
 & && \mathbf{y} \in \mathcal{S} = \arg \min_{\mathbf{y}} \{\Omega(\mathbf{x}, \mathbf{y}) : \mathbf{y} \in \mathcal{C}(\mathbf{x})\}
 \end{aligned}$$

where $\mathbf{x} \in \mathbb{R}^n$, $\mathbf{y} \in \mathbb{R}^m$, are decisions vectors, and $\Phi(\mathbf{x}, \mathbf{y}) : \mathbb{R}^{n+m} \rightarrow \mathbb{R}$ and $\Omega(\mathbf{x}, \mathbf{y}) : \mathbb{R}^{n+m} \rightarrow \mathbb{R}$ are the objective functions of the upper- and the lower-level problems, respectively. \mathcal{Z} is the joint feasible region of the upper-level problem and $\mathcal{C}(\mathbf{x})$ the feasible region of the lower-level problem induced by \mathbf{x} . In the existing market models that adopt a hierarchical

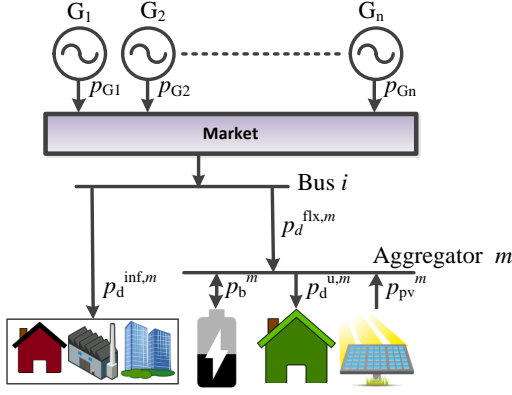


Fig. 2. Structure of the proposed modeling framework.

approach, the coupling variable \mathbf{y} is the electricity price (e.g. [19], [22]). That is, the upper-level (the wholesale market in our case) determines the price schedule, while the lower-level (the aggregator acting on behalf of the prosumers), optimizes its consumption based on this price schedule.

Fig. 2 shows the structure of the proposed modeling framework. The demand model consists of two parts: (i) *inflexible* demand, $p_d^{\text{inf},m}$, with a fixed demand profile, representing large industrial loads and loads without flexible resources; and (ii) *flexible* demand, $p_d^{\text{flx},m}$, comprising a large population of prosumers who collectively maximize self-consumption. Note that not every bus in the system has a load connected to it, hence the distinction between an aggregator $m \in \mathcal{M}$ and bus $i \in \mathcal{B}$. Unlike in most existing studies, the interaction between the wholesale market and the aggregators in our model is through the demand profile of the aggregator, $p_d^{\text{flx},m}$. Note that in contradistinction to the price-taking assumption when the electricity price is known in advance, now the collective action of the prosumers affects the wholesale market dispatch, which is the salient feature of the proposed model.

C. Upper-level Problem (Wholesale Market)

To emulate the market outcome, the upper-level problem is cast as a unit commitment (UC) problem aiming to minimize the generation cost:

$$\text{minimize}_{s,u,d,p,\theta} \sum_{g \in \mathcal{G}} \sum_{h \in \mathcal{H}} (c_g^{\text{fix}} s_{g,h} + c_g^{\text{su}} u_{g,h} + c_g^{\text{sd}} d_{g,h} + c_g^{\text{var}} p_{g,h}), \quad (1)$$

where $s_{g,h}, u_{g,h}, d_{g,h} \in \{0, 1\}$, $p_{g,h} \in \mathbb{R}_+$, $\theta_{i,h} \in \mathbb{R}$ are the decision variables of the problem. The problem is subject to the following constraints:

$$\sum_{g \in \mathcal{G}_i} p_{g,h} = \sum_{m \in \mathcal{M}_i} (p_d^{\text{inf},m} + p_d^{\text{flx},m}) + \sum_{l \in \mathcal{L}_i} (p_{l,h} + \Delta p_{l,h}), \quad (2)$$

$$|B_{i,j}(\theta_{i,h} - \theta_{j,h})| \leq \bar{p}_l, \quad (3)$$

$$\underline{p}_g s_{g,h} \leq p_{g,h} \leq \bar{p}_g s_{g,h}, \quad (4)$$

$$u_{g,h} - d_{g,h} = s_{g,h} - s_{g,h-1}, \quad (5)$$

$$\sum_{g_{\text{synch}} \in \mathcal{R}} \bar{p}_g s_{g,h} \geq \sum_{m \in \mathcal{M}_r} (p_d^{\text{inf},m} + p_d^{\text{flx},m}) + p_{r,h}^{\text{res}}, \quad (6)$$

$$u_{g,h} + \sum_{\tilde{h}=0}^{\tau_g^u-1} d_{g,h+\tilde{h}} \leq 1, \quad (7)$$

$$d_{g,h} + \sum_{\tilde{h}=0}^{\tau_g^d-1} u_{g,h+\tilde{h}} \leq 1, \quad (8)$$

$$-r_g^- \leq p_{g,h} - p_{g,h-1} \leq r_g^+, \quad (9)$$

where (2) is the power balance equation at each bus i in the system², with \mathcal{G}_i , \mathcal{M}_i , \mathcal{L}_i representing respectively the sets of generators, aggregators and lines connected to bus i , and $p_d^{\text{inf},m}$, $p_d^{\text{flx},m}$, $p_{l,h}^{i,j}$ and $\Delta p_{l,h}^{i,j}$ representing respectively the inflexible and flexible demand of aggregator m , line power and line power loss (assumed to be 10% of the line flow) on each line connected to bus i ; (3) represents line power limits; (4) limits the dispatch level of a generating unit between its respective minimum and maximum limits; (5) links the status of a generator unit to the up and down binary decision variables; (6) ensures spinning reserves for system stability are provided in reach region of the grid, with \mathcal{M}_r being the set of aggregators in region r ; (7) and (8) ensure minimum up and minimum down times of the generators; and (9) are the generator ramping constraints.

D. Lower-level Problem (Aggregators)

Prosumer aggregation is formulated in the lower-level problem. The loads within an aggregator's domain are assumed homogeneous, which allows us to represent the total aggregator's demand with a single load model. The electricity price is not explicitly shown in the optimization problem³ (see Assumptions 1 and 2 in Section II.A). Note that in a HEM problem [29], the electricity price is known ahead of time, resulting in a price-anticipating behavior. In our framework, the electricity price is a by-product of the specific mechanism adopted for DR aggregation and is dynamic. In a practical implementation, a HEM system is an agent acting on behalf of the prosumer. Given a sufficient battery capacity, the end-users' comfort is not jeopardized.

The lower-level problem is formulated as follows:

$$\text{minimize}_{p_b} \sum_{h \in \mathcal{H}} p_{d,h}^{\text{flx},m}, \quad (10)$$

where the battery power $p_{b,h}^m \in \mathbb{R}$ is the decision variable. The problem is subject to the following constraints:

$$p_{d,h}^{\text{flx},m} = p_{d,h}^{u,m} - p_{p_v,h}^m + p_{b,h}^m, \quad (11)$$

$$\underline{p}_b^m \leq p_{b,h}^m \leq \bar{p}_b^m, \quad (12)$$

$$\underline{e}_b^m \leq e_{b,h}^m \leq \bar{e}_b^m, \quad (13)$$

$$e_{b,h}^m = \eta_b^m e_{b,h-1}^m + p_{b,h}^m, \quad (14)$$

where (11) is the power balance equation; and (12)-(14) are the battery storage constraints. Power $p_{d,h}^{u,m}$ is the underlying demand of the prosumers. Note that according to the Assumption 3 in Section II.B, except for battery losses, the underlying *energy* demand doesn't change, however the instantaneous *power* can. Finally, the Karush-Kuhn-Tucker optimality conditions of the lower-level problem are added as

²Note that the flexible demand of each aggregator m , $p_d^{\text{flx},m}$, couples the upper-level (wholesale market) problem with each of the m lower-level (aggregator) problems.

³In a practical implementation, the electricity price could consist of the dual variables associated with the power balance constraint (2) and power flow constraints (3) of the upper-level problem, plus retail and network charges.

the constraints to the upper-level problem, which reduces the problem to a single mixed integer linear program that can be solved using of-the-shelf solvers. Note that because the two levels interacts through a power, not through a price, unlike in [19], no linearization is required.

III. CASE STUDIES

To showcase the efficacy of the model, we analyze steady-state voltage stability of a simplified model of the NEM with scenarios reflecting different prosumer penetrations.

A. Model of the Australian National Electricity Market (NEM)

The 14-generator IEEE test system shown in Fig. 3 was initially proposed in [31] as a test bed for small-signal analysis. The system is loosely based on the NEM, the interconnection on the Australian eastern seaboard. The network is stringy, with large transmission distances and loads concentrated in a few load centers. It consists of 59 buses, 28 loads, and 14 generators. The test system consists of four areas representing the states of Queensland, New South Wales, Victoria and South Australia, and 28 aggregators, one for each load bus. The generator technologies and modeling assumptions follow [24]. We consider two RES penetration rates. In the business as usual (BAU) scenario, the generation portfolio includes 39.36 GW coal, 5.22 GW gas, and 2.33 GW hydro. In the high-RES scenario, 40% of the total demand is covered by variable RES. Inspired by two recent Australian 100% renewables studies [6], [10], part of coal generation is replaced with wind and utility PV using wind and solar traces from the AEMO's planning document [32], which results in 28.94 GW coal, 5.22 GW gas, 2.33 GW hydro, 21 GW wind, and 12 GW utility PV. Given the deterministic nature of the model, we assume 10% reserves for each region in the system to cater for demand and RES forecast errors. In market simulations, generators are assumed to bid according to their short-run marginal costs, while RESs bid at zero cost. Simulations are performed using a rolling horizon approach with hourly resolution assuming a perfect foresight. The optimization horizon is three days with a two-day overlap. Last, wind and solar generators are assumed to operate in a voltage control mode.

B. Prosumer Scenarios

We assume four different prosumer penetrations: zero, low, medium and high. With no prosumer penetration, the demand is assumed inflexible. For the other three scenarios, we assume that part of the demand is equipped with small-scale (residential and small commercial) PV-battery systems. The uptake of PV loosely follows a recent AEMO study [33]. The PV capacities are respectively 5 GW, 10 GW, and 20 GW for the low, medium and high uptake of prosumers (the existing penetration in the NEM is 5 GW). We consider three different amounts of storage: zero, 2 kW h, and 4 kW h of storage for 1 kW of rooftop PV.⁴ Hourly demand and PV traces are from the AEMO's planning document [32].

⁴A typical ratio in the NEM today is 2 h of storage [33], however, in the future, this will likely increase due to the anticipated cost reduction.

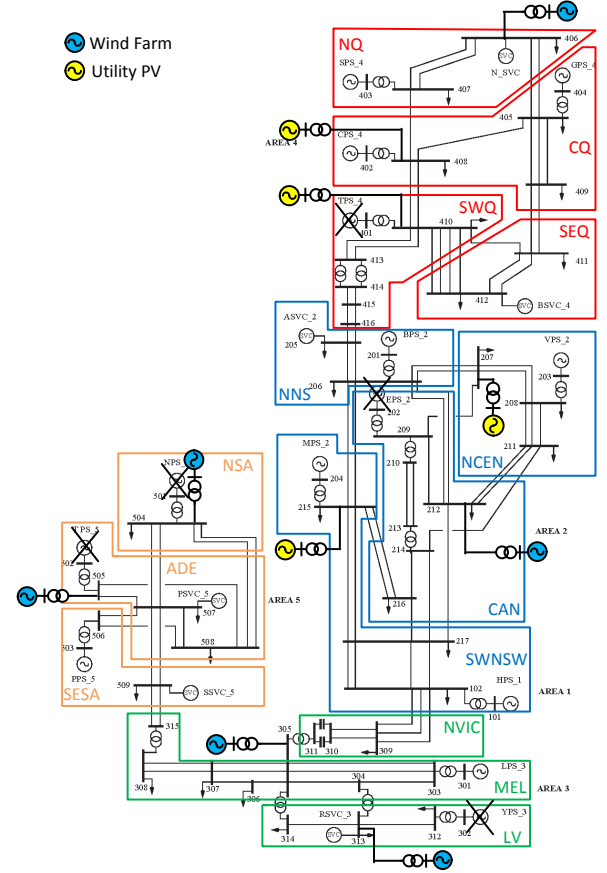


Fig. 3. Single-line diagram of the 14-generator model of the NEM with the 16 zones that define wind and solar traces [32].

C. Dispatch Results

Dispatch results for a typical summer week with high demand (12-15 January) for a few representative scenarios are shown in Figs. 4 and 5. The figures show, respectively, generation dispatch results (top row), combined flexible demand of all aggregators (middle row), and a combined battery charging profile of all aggregators (bottom row). Fig. 4 shows results for a medium prosumer penetration with, respectively, zero, 2 h and 4 h hours of storage. Fig. 5 shows results for different prosumer penetrations (zero, medium, high) with 4 h of storage. Observe that in all six cases peak demand occurs at mid-day due to a high air-conditioning load. After the sunset, however, the demand is still high, so gas generation is needed to cover the gap. In the available generation mix, gas has the highest short-run marginal cost, which increases the electricity price in late afternoon/early evening. The balancing results over the simulated year have revealed that the increased RES penetration in the renewable scenarios requires more energy from gas generation compared to the BAU scenario. This is due to RES intermittency, and the ramp limits of conventional coal-fired generation. An increased penetration of prosumers with higher amounts of storage, however, reduces the usage of gas due to a flatter demand profile.

Observe in Fig. 4 how an increasing amount of storage increases prosumers' self-sufficiency. Without storage, the load is supplied by PV during the day, and the rest is supplied

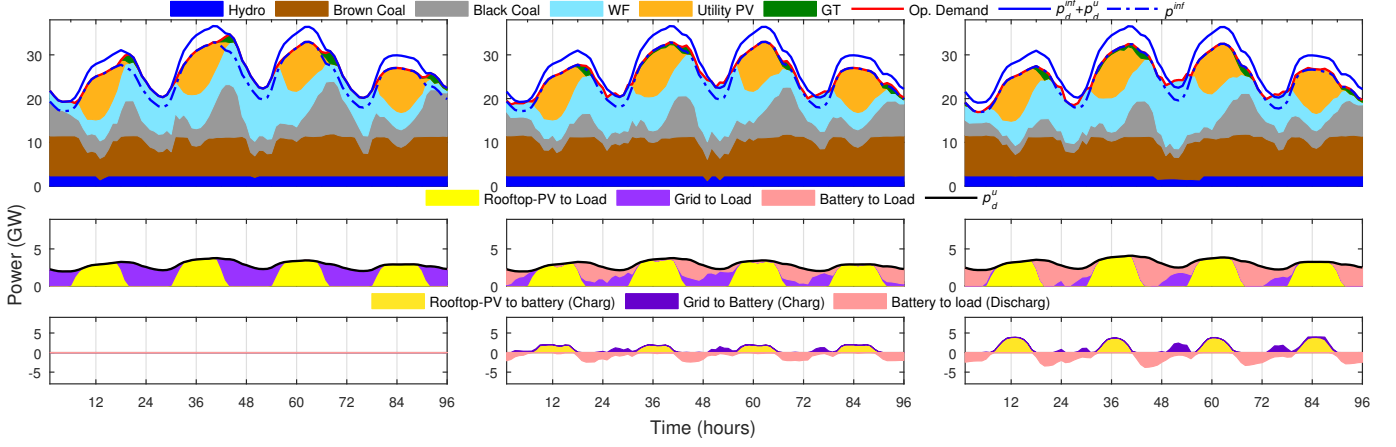


Fig. 4. Dispatch results for a typical summer week with high demand (12-15 January) for a medium prosumer penetration with different amounts of storage: zero (left), 2 h (middle) and 4 h (right).

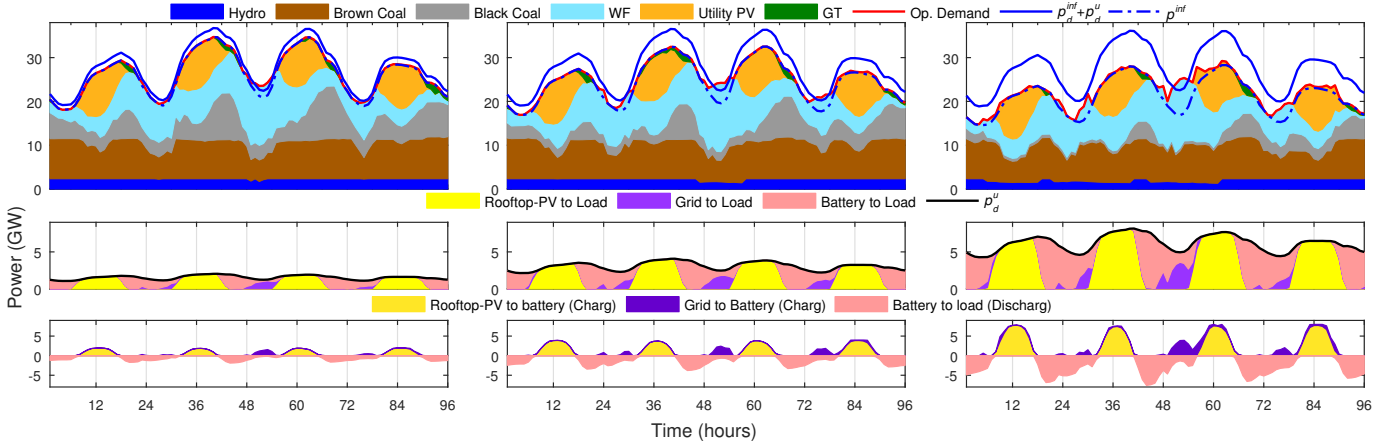


Fig. 5. Dispatch results for a typical summer week with high demand (12-15 January) for different penetrations of prosumers with 4 h of storage: zero (left), medium (middle), high (right).

from the grid. When storage is added to the system, batteries are charged when electricity is cheap (mostly from rooftop PV during the day and from wind during the night) and discharged in late afternoon to offset the demand when the electricity is most expensive. Note that the plots in the bottom two rows show a combined load profile of all aggregators in the system, which explains why storage is seemingly charged and discharged simultaneously. Observe how high amounts of storage (rightmost columns in Figs. 4 and 5) flatten the demand profile. During the day, the flexible demand is supplied by rooftop PV, which *reduces* the operational demand, while during the night, with sufficient wind generation, batteries are charged, which *increases* the operational demand. This has a significant beneficial effect on loadability and voltage stability, as discussed in the next section.

D. Loadability and Voltage Stability Results

Dispatch results from the market simulations are used to perform a load flow analysis, which is then used in the assessment of loadability and voltage stability. In the analysis, only scenarios with 4 h of storage were considered. The

prosumer scenarios are thus called, according to the respective penetration rates, zero (ZP), low (LP), medium (MP), and high (HP). Note that the market model only considers a simplified DC power flow with the maximum angle limit set to 30° . This can sometimes result in a non-convergent AC power flow in scenarios with a high RES penetration. The number of non-convergent hours is, respectively, 175, 37, 12, and 0, in scenarios ZP, LP, MP, and HP. An increased penetration of prosumers thus improves voltage stability, as explained in more detail later.

In loadability assessment, N-1 security is considered, so a contingency screening is performed first. We screened all credible N-1 contingencies to identify the most severe ones based on the maximum power transfer level [34]. Twenty most critical contingencies were selected for each hour of the simulated year.

1) *Loadability calculation:* To calculate system loadability (LDB), power flow is solved twice using the market dispatch results; first for the base case and then for each of the preselected critical contingency. When the load flow does not converge for a particular contingency, the last convergent load flow solution without a contingency is considered the

TABLE I
LOADABILITY RESULTS

	LDB Cases	Scenarios				
		BAU	ZP	LP	MP	HP
Avg. LDB margin (GW)	NEM	7.8	2.5	4.3	5.9	7.1
	SA/VIC	2.2	0.8	1.1	1.5	1.7

loadability margin. We considered two different load increase patterns, where load and generation are increased uniformly, in proportion to the base case: (i) **NEM**: only load and generation in the NEM are increased; (ii) **SA/VIC**: only load in VIC and generation in SA are increased. The results are summarized in Table I. Comparing the BAU scenario and the renewable scenario with conventional demand (ZP), it can be seen that with the increased RES penetration, the average loadability margin over the simulated year in the demand increase scenario NEM is decreased from 7.8 GW to 2.5 GW. Similarly, the average loadability margin in the demand increase scenario SA/VIC is reduced from 2.2 GW to 0.8 GW. With a high RES penetration, conventional synchronous generation is replaced by inverter-based generation with inferior reactive power support capability⁵, which results in a reduced reactive power margin in the system and hence lower stability margin. With an increased penetration of prosumers, the system loadability improves. Observe that the average system loadability margin in both load increase scenarios, NEM and SA/VIC, is increased from 2.5 GW and 0.8 GW for the renewable scenario with no prosumers (ZP) to 7.1 GW and 1.7 GW for high penetration of prosumers (HP), respectively, which indicates a considerable improvement in the system loadability margin. This is explained by a demand reduction when prosumer demand is supplied by rooftop PV. In the night hours, however, even with high prosumer penetration, the loadability can be reduced when prosumers charge their batteries, as observed in Figs. 4 and 5. The situation is further illustrated in Fig. 6 that compares the loadability margin for the load increase scenario NEM and the results of the modal analysis, discussed next.

2) *Modal analysis*: Using the market dispatch results, modal analysis of the reduced V-Q sub-matrix of the power flow Jacobian is performed to assess voltage stability. The smallest real part of the V-Q sub-matrix' eigenvalues is used as a relative measure of the proximity to voltage instability. Furthermore, the associated eigenvectors provide information on the critical voltage modes and the weak points in the grid, that is, the areas that are most prone to voltage instability. The results are summarized in Table II. With the increased RES penetration, the average of the minimum of the real part of all eigenvalues, henceforth called the minimum eigenvalue, is reduced from 49.5 Np/s for the BAU scenario to 42.3 Np/s for the ZP scenario. With an increased prosumer penetration, the average of the minimum eigenvalue over the simulated year increases from 42.3 Np/s (ZP) to 48.8 Np/s (HP). Observe in

TABLE II
MODAL ANALYSIS RESULTS

	Scenarios				
	BAU	ZP	LP	MP	HP
Avg. of minimum Real(eig) (Neper/s)	49.5	42.3	44.8	45.6	48.4
Nodes with highest participation factor in critical voltage modes	506	506	506	505	505
	306	505	505	506	410
	308	410	410	410	408
Unstable hours	0	175	37	12	0

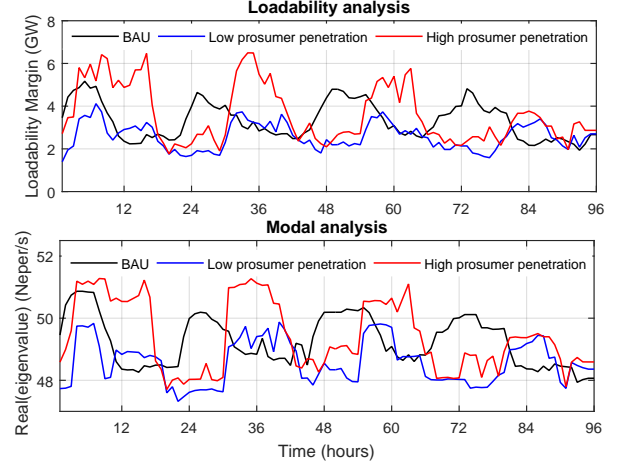


Fig. 6. Comparison of the loadability and modal analysis results for a typical summer week with high demand (12-15 January) for the load increase scenario NEM for BAU, and low and high prosumer penetration.

Fig. 6 that the results of the modal analysis confirm the results loadability analysis. The general trend remains the same; higher RES penetration with conventional demand reduces the minimum real value of an eigenvalue, which implies a lower voltage stability margin.

Another observation that can be made from the modal analysis concerns the location of the weak points in the system, that is, the buses with the highest participation factor in the critical voltage modes. These clearly change with the increased RES penetration. In the BAU Scenario, the weakest points are typically buses with large loads (e.g. 306 and 308, representing Melbourne). With the increased RES penetration and no prosumers (ZP), however, the weakest part of the system become buses located close to RESs (e.g. 505 and 410, representing, respectively a large wind farm in SA and a large solar PV farm in QLD).

Further, we observed that the voltage stability margin in the system improves significantly when there are more synchronous generators in the grid, due to their superior reactive power support capability compared to RES. The participation factor analysis of the renewable scenarios revealed that SA and QLD are the most voltage constrained regions where the penetration of WFs and utility PVs is higher compared to other regions in the NEM, which can be, to a large extent, mitigated with a sufficiently large penetration of prosumers. This clearly illustrates that RESs and prosumers change power system stability in ways that have not been experienced before, which requires a further in-depth analysis.

⁵For synchronous generation, a 0.8 power factor is assumed. For RES, we used the reactive power capability curve for the generic GE Type IV wind farm model [35], in which the reactive power generation is significantly constrained close to the nominal active power generation.

IV. CONCLUSION

The emergence of demand side technologies, in particular rooftop PV, battery storage and energy management systems is changing the way electricity consumers source and consume electric power, which requires new demand models for the long-term analysis of future grids. In this paper, we propose a generic demand model that captures the aggregate effect of a large number of prosumers on the load profile that can be used in market simulation. The model uses a bi-level optimization framework, in which the upper level employs a unit commitment problem to minimize generation cost, and the lower level problem maximizes collective prosumers' self-consumption. To that effect, the model implicitly assumes an efficient mechanism for demand response aggregation, for example peer-to-peer energy trading or any other form of transactive energy. Given that any efficient mechanism for demand response aggregation that aims to minimize generation cost will utilize self-generation first, the self-consuming assumption appears reasonable at the level of abstraction assumed in long-term future grid scenario analysis. Moreover, the model is generic in that it does not depend on specific practical implementation details that will vary in the long-run.

To showcase the efficacy of the proposed model, we study the impact of prosumers on the performance, loadability and voltage stability of the Australian NEM with a high RES penetration. The results show that an increased prosumer penetration flattens the demand profile, which increases loadability and voltage stability, except in situations with a low underlying demand and an excess of RES generation, where the aggregate demand might increase due to battery charging. The analysis also revealed that with a high RES penetration, the weakest points in the network move from large load centers to areas with high RES penetration. Also, loadability and voltage stability are highly dependent on the amount of synchronous generation due to their superior reactive power capability compared to RES, which requires further analysis.

REFERENCES

- [1] EPRI, "The Integrated Grid Realizing the Full Value of Central and Distributed Energy Resources," Tech. Rep., 2014.
- [2] Morgan Stanley, "Australia Utilities Asia Insight: Solar & Batteries," Tech. Rep., 2016.
- [3] Energy Networks Australia and CSIRO, "Electricity Network Transformation Roadmap: Key Concepts Report," Tech. Rep. December, 2016.
- [4] CSIRO, "Future Grid Forum: Change and Choice for Australian Electricity System," Tech. Rep., 2013.
- [5] B. Kampman, M. Afman, and J. Blommerde, "The potential of energy citizens in the European Union," CE Delft, Tech. Rep., 2016.
- [6] M. Wright and P. Hearps, "Zero Carbon Australia Stationary Energy Plan," The University of Melbourne Energy Research Institute, Tech. Rep., 2010.
- [7] B. Elliston, I. MacGill, and M. Diesendorf, "Least Cost 100% Renewable Electricity Scenarios in the Australian National Electricity Market," *Energy Policy*, vol. 59, pp. 270–282, Aug. 2013.
- [8] C. Budischak, and et al., "Cost-Minimized Combinations of Wind Power, Solar Power and Electrochemical Storage, Powering the Grid up to 99.9% of the Time," *Journal of Power Sources*, vol. 225, pp. 60–74, Mar. 2013.
- [9] I. G. Mason, S. C. Page, and A. G. Williamson, "A 100% renewable electricity generation system for New Zealand utilising hydro, wind, geothermal and biomass resources," *Energy Policy*, vol. 38, pp. 3973–3984, Aug. 2010.
- [10] Australian Energy Market Operator (AEMO), "100 per cent renewable study - modelling outcomes," Tech. Rep., 2013.
- [11] L. Fahey and R. M. Randall, *Learning From the Future*. Wiley, 1998.
- [12] J. Foster, C. Froome, C. Greig, O. Hoegh-Guldberg, P. Meredith, L. Molyneaus, T. Saha, L. Wagner, and B. Ball, "Delivering a competitive Australian power system Part 2: The challenges, the scenarios," Tech. Rep. Oct, 2013.
- [13] G. Sanchis, "e-Highway2050: Europe's future secure and sustainable electricity infrastructure. Project results," Tech. Rep., 2015.
- [14] M. Hand, S. Baldwin, E. DeMeo, J. Reilly, T. Mai, D. Arent, G. Porro, M. Meshek, and D. Sandor, "Renewable Electricity Futures Study," National Renewable Energy Laboratory (NREL), Tech. Rep., 2012.
- [15] B. Elliston, J. Riesz, and I. MacGill, "What cost for more renewables? The incremental cost of renewable generation An Australian National Electricity Market case study," *Renewable Energy*, vol. 95, pp. 127 – 139, 2016.
- [16] H. Marzoghi, D. J. Hill, and G. Verbič, "Performance and stability assessment of future grid scenarios for the Australian NEM," in *2014 Australasian Universities Power Engineering Conference (AUPEC)*, Sep 2014.
- [17] F. Ramos, C. Cañizares, and K. Bhattacharya, "Effect of price responsive demand on the operation of microgrids," in *18th International Conference on the Power Systems Computation (PSCC 2014)*, Aug 2014.
- [18] K. Bruninx, D. Patteeuw, E. Delarue, L. Helsen, and W. D'haeseleer, "Short-term demand response of flexible electric heating systems: The need for integrated simulations," in *10th International Conference on the European Energy Market (EEM 2012)*, May 2012.
- [19] M. Zugno, J. Miguel Morales, P. Pinson, and H. Madsen, "A bilevel model for electricity retailers' participation in a demand response market environment," *Energy Economics*, vol. 36, pp. 182 – 197, 2013.
- [20] S. Mathieu, Q. Louveaux, D. Ernst, and B. Cornuesse, "A quantitative analysis of the effect of flexible loads on reserve markets," in *18th International Conference on the Power Systems Computation (PSCC 2014)*, Aug 2014.
- [21] O. Mégel, J. L. Mathieu, and G. Andersson, "Scheduling distributed energy storage units to provide multiple services under forecast error," *International Journal of Electrical Power & Energy Systems*, vol. 72, pp. 48 – 57, 2015.
- [22] M. Gonzalez Vaya, and G. Andersson, "Optimal bidding strategy of a plug-in electric vehicle aggregator in day-ahead electricity markets under uncertainty," *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2375–2385, Sep 2015.
- [23] S. Teske, T. Brown, E. Tröster, P.-P. Schierhorn, and T. Ackermann, "PowE[R] 2030 - A European Grid for 3/4 Renewable Energy by 2030," Greenpeace Germany, Tech. Rep., 2014.
- [24] H. Marzoghi, G. Verbič, and D. J. Hill, "Aggregated demand response modelling for future grid scenarios," *Sustainable Energy, Grids and Networks*, vol. 5, pp. 94 – 104, 2016.
- [25] S. Riaz, H. Marzoghi, G. Verbič, A. C. Chapman, and D. J. Hill, "Impact study of prosumers on loadability and voltage stability of future grids," in *2016 IEEE International Conference on Power System Technology (POWERCON)*, 2016.
- [26] P. Kundur, *Power System Stability and Control*. EPRI Power System Engineering Series, McGraw-Hill, 1994.
- [27] T. Van Cutsem, and C. Vournas, *Voltage Stability of Electric Power Systems*, ser. Kluwer international series in engineering and computer science. Springer, 1998.
- [28] H. Marzoghi, D. J. Hill, and G. Verbič, "Aggregated Effect of Price-Taking Users Equipped with Emerging Demand-Side Technologies on Performance of Future Grids," in *2016 IEEE International Conference on Power System Technology (POWERCON)*, 2016.
- [29] H. Tischer, and G. Verbič, "Towards a Smart Home Energy Management System-A Dynamic Programming Approach," in *Innovative Smart Grid Technologies Asia*, 2011.
- [30] A. C. Chapman, G. Verbič, and D. J. Hill, "Algorithmic and strategic aspects to integrating demand-side aggregation and energy management methods," *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2748–2760, Nov 2016.
- [31] M. Gibbard, and D. Vowles, "Simplified 14-generator model of the SE Australian power system," The University of Adelaide, Tech. Rep., 2010.
- [32] Australian Energy Market Operator (AEMO), "2012 NTNDP Assumptions and Inputs," Tech. Rep., 2012.
- [33] —, "Emerging Technologies Information Paper, National Electricity Forecasting Report," Tech. Rep., 2015.
- [34] E. Vaahedi, C. Fuchs, W. Xu, Y. Mansour, H. Hamadanizadeh, and G. K. Morison, "Voltage stability contingency screening and ranking," *IEEE Transactions on Power Systems*, vol. 14, no. 1, pp. 256–265, Feb 1999.
- [35] K. Clark, N. W. Miller, and J. J. Sanchez-Gasca, "Modeling of GE Wind Turbine Generators for Grid Studies," Tech. Rep., 2013.